

STC: Coarse-Grained Vehicular Data Based Travel Speed Sensing by Leveraging Spatial-Temporal Correlation

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Abstract—As an important information for traffic condition evaluation, trip planning, transportation management, *etc.*, average travel speed for a road means the average speed of vehicles travelling through this road in a given time duration. Traditional ways for collecting travel-speed oriented traffic data always depend on dedicated sensors and supporting infrastructures, and are therefore financial costly. Differently, vehicular crowdsensing as an infrastructure-free way, can be used to collect data including real-time locations and velocities of vehicles for road travel speed estimation, which is a quite low-cost way. However, vehicular crowdsensing data is always coarse-grained. This coarseness can lead to the incompleteness of travel speeds. Aiming to handle this problem as well as estimate travel speed accurately, in this paper, we propose an approach named STC that exploits the *spatial-temporal correlation* among travel speeds for roads by introducing the time-lagged cross correlation function. The *time lagging factor* describes the time consumption of traffic feature diffusion along roads. To properly calculate cross correlation, we novelly make the determination of the time lagging factor self-adaptive by recording the locations of vehicles at different roads. Then, utilizing the local stationarity of cross correlation, we further reduce the problem of single-road travel speed vacancy completion to a minimization problem. Finally, we fill all the vacancies of travel speed for roads in a recursive way using the geometric structure of road net. Elaborate experiments based on real taxi trace data show that STC can settle the incompleteness problem of vehicle crowdsensing data based travel speed estimation and ensure the accuracy of estimated travel speed better, in comparison with representative existing methods such as KNN, Kriging and ARIMA.

Index Terms—Travel Speed Estimation, Vehicular Crowdsensing, Spatial-Temporal Correlation.

I. INTRODUCTION

Average travel speed for a road means the average speed of vehicles travelling through this road in a given time duration. Such information can be used for traffic condition evaluation, trip planning, transportation management, and so on. Providing services based on average travel speed is very helpful both for drivers and traffic controllers. To get travel speed information, in traditional ways, the road net is monitored by infrastructure-supported devices such as cameras [1], [2], loop detectors [3], [4] and radio sensors [5] which are very expensive to deploy and maintain [6]. What's more, these ways can be affected by environment. For example, quality of camera-based data is vulnerable to weather condition, light condition, and so on.

Different from infrastructure-based ways, vehicular crowdsensing is an up-to-the-moment infrastructure-free way for traffic data collection. Vehicles running on roads can incidentally offer their data including timestamps, locations and real-time speeds to a central server via wireless

communication. The feasibility of vehicular crowdsensing is guaranteed by the wide deployment of on-board GPS and wireless communication devices such as navigation facilities. Since it almost needs no additional equipment, the cost of vehicular crowdsensing is greatly low when compared with infrastructure-based methods. We can use vehicular crowdsensing data to estimate travel speeds for roads. However, vehicular crowdsensing data is usually coarse-grained. The first reason is that not all the vehicles running on roads will be willing to offer data. The second reason is the temporal variation of spatial distribution of vehicles. Take it as an example, in morning rush hour, most roads can be covered by vehicles while much less roads can be covered in midnight. The coarseness of vehicular crowdsensing data will lead to the incompleteness problem of travel speeds of roads, which can be testified by analysis of real taxi probe data. In addition, to guarantee the usability of travel speeds, the estimated values have to meet predefined accuracy requirement.

In order to handle the incompleteness problem of vehicular crowdsensing data based travel speed estimation and to calculate travel speed accurately, in this paper, we propose a spatial-temporal correlation based approach named STC (Spatial Temporal Correlation). In STC, we leverage the spatial-temporal correlation of travel speeds among roads. Our basic argument is that the travel speeds of roads close to each other are correlated due to spatial proximity of these roads. More specifically, we use the time-lagged cross correlation function to measure the relevances between travel speeds of different roads for different calculation intervals. Note that due to the time consumption for vehicles to run from road r_1 to r_2 , within a relative small area, the farther the distance between two roads is, the longer the time taken by a traffic characteristic to spread from r_1 to r_2 will be. We call this time consumption as *time lagging factor*. Particularly, we employ the traceability of vehicle locations to determine the time lagging factor self-adaptively, which is helpful to properly calculate the cross correlation between roads. Having the cross correlation, we fill the vacancy of single-road travel speed with the help of the near-by roads whose travel speeds are not empty. We accomplish this by converting it to a minimization problem, using the local stationarity of cross correlation between roads. Finally, we fill all the travel speed vacancies of roads in a recursive way by utilizing the geometric structure of road net.

To examine the effectiveness of our approach, we conduct experiments based on real taxi trace data including

8363 taxis, collected in Shenzhen, China during 18-26, April, 2011. Through cross-validation, we show that our approach can handle the incompleteness of travel speeds and guarantee the accuracy of travel speed calculation better, compared with classical estimation methods such as KNN, Kriging and ARIMA.

The main contributions of this paper are as follows:

- We propose a spatial-temporal correlation based approach named STC to estimate travel speed based on coarse-grained vehicular crowdsensing data, in which we use time-lagged cross correlation function to measure the correlation among roads in terms of travel speeds.
- To properly calculate cross correlation, we novelly make the determination of time lagging factor self-adaptive by leveraging the traceability of vehicle locations at upstream and downstream roads.
- We reduce the problem of single-road travel speed vacancy completion to a minimization problem by using the local-stationarity of cross correlation. Then by utilizing the topology of road net, we use a recursive way to fill all the travel speed vacancies of roads.

The rest of this paper is organized as follows. In Section II, we make a review of existing works that related to ours. In Section III, we formulate the problem that we aim to handle. Then in Section IV we introduce our design of STC for travel speed estimation in detail. Next, we show our experimental evaluation results and give a discussion of the use of our method for future travel speed prediction in Section V. Finally, our conclusion and future work will be discussed in Section VI.

II. RELATED WORK

We review existing works related to ours in following aspects:

Vehicular Crowdsensing. There are works that examined the use of vehicles for certain applications. For example, Bauza *et al.* [7] proposed a vehicular multi-hop end-to-front local traffic congestion level detection strategy. Du *et al.* [8] aimed to effectively monitor congestion by floating cars whose routes are optimized to sense data in a wide geographical range. Hu *et al.* [9] designed a role-transferring mechanism for on-board phones to optimize communication performance in vehicle-based participatory sensing applications. Thiagarajan *et al.* [10] proposed to track mobile phone locations to estimate road traffic delay, which was an energy-efficient way. Sun *et al.* [11] used cognitive radio vehicular networks to enable emergency communication between vehicles. Coric *et al.* [12] used crowdsensing to sketch the map of on-street parking spaces to help drivers to find parking positions. Chen *et al.* [13] took privacy into consideration while used participatory sensing to draw high quality city map. None of above works inspected travel speed estimation while it was done by Wang *et al.* [14] who only paid attention to freeways, rather than ordinary roads. And Aslam *et al.* [6] used taxis as probes to estimate traffic volume with the help of logistic regression and linear regression. But none of above existing works applied vehicular crowdsensing into the wide range travel speed calculation.

Vacancy Completion Methods. The incompleteness problem is a critical problem in vehicle-collected data. To handle this problem, different works in the literature used various methods. For example, Alasmay *et al.* [15] used branch and bound approximation algorithm to select optimal number of vehicles for collecting data when wireless channel capacity is limited. And compressive sensing was considered by works such as [16] [17] [18] to collect and recover vehicle-related data. However, the computational complexity of compressive sensing is always high. Matrix completion was also used as an incomplete data estimation method in the work of Du *et al.* [8], which was also of high calculation cost. What's more, we mainly focus on single-calculation-interval vacancies completion which is more like a single-column vector, rather than a multi-column matrix. Taking spatial correlation of roads into consideration, Zou *et al.* [19] proposed to use Kriging interpolation to complete the data where no detection equipment such as loop detector is deployed. Correlation among roads was better used by Aslam *et al.* [6] who introduced the similarity of roads. However, the temporal correlation among roads was overlooked by them.

III. PROBLEM FORMULATION

In this section, we first make clear the formalization of road net, based on which we state the problem of coverage incompleteness according to taxi trace statistics. Then we explain the goal of travel speed calculation.

A. Road Net Formalization

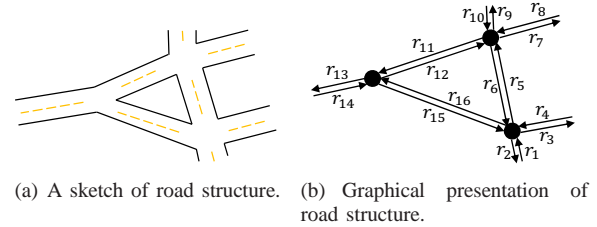


Fig. 1: Illustration of road net formalization.

Fig.1(a) is a sketch of a fraction of real road net. It consists of *road segments* and *intersections*. A road segment is a portion of road that has only one entrance and only one exit and vehicles are only allowed to run from this entrance to this exit under transportation regulations. An intersection is a point connecting adjacent road segments. For conciseness, we use directed graph to present the road net. A vertex in this graph represents an intersection in real road net while an edge represents a road segment. We use \mathcal{G} to represent the graph of the whole road net, \mathcal{R} to represent the edge set of \mathcal{G} , and \mathcal{V} to represent its vertex set. Fig.1(b) is the graphical form of Fig.1(a), where $r_i \in \mathcal{R}, i = 1, 2, \dots, 16$.

B. Problem of Coverage Incompleteness in Vehicular Crowdsensing

As aforementioned, we use vehicular crowdsensing to collect traffic data. The data containing *timestamp*, *longitude*, *latitude*, *velocity* of a vehicle will be offered at will by this vehicle via wireless communication. We formally

call a piece of data in this form as a *record*. We examine real trace data of taxis in Shenzhen, China to first show the spatial gain of our approach and then show the still-existing spatial-temporal vacancies. There are 8363 taxis that participated in this work of data collection from April 18th 00:00:00, 2011 to April 26th 00:00:00, 2011. Fig.2 illustrates a snapshot of the spatial distribution of these taxis. Intuitively, we can see that the roads reached by taxis are not limited to main roads.

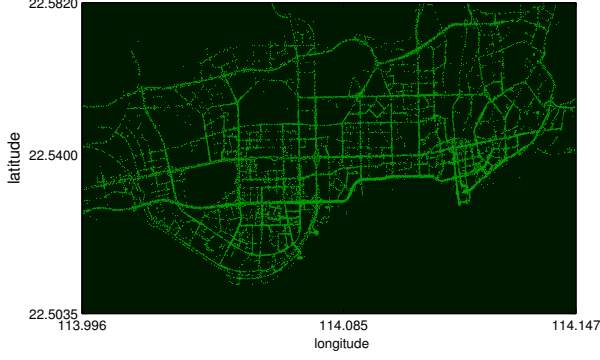


Fig. 2: A snapshot of taxi distribution.

However, given the length of calculation interval T , owing to the mobility of vehicles, the number of collected records that can be used to directly calculate the travel speeds for different road segments will vary in different intervals. For i^{th} road segment $r_i \in \mathcal{R}$, in j^{th} calculation interval t_j , we denote this number as n_{ij} . For trust consideration, only when n_{ij} is equal or bigger than a predefined threshold integer $N_{thr}(T)$, we can calculate the travel speed for r_i directly. So we define,

Definition 1: Road segment r_i is covered in j^{th} calculation interval t_j if $n_{ij} \geq N_{thr}(T)$.

Let N_R denote the total number of road segments in \mathcal{R} . Based on our road net formalization, we have 1882 road segments in the central area of Shenzhen, which gives $N_R = 1882$. Then we denote the number of road segments that are covered in t_j as N_c . Fig.3 shows the variation of N_c with different T and N_{thr} .

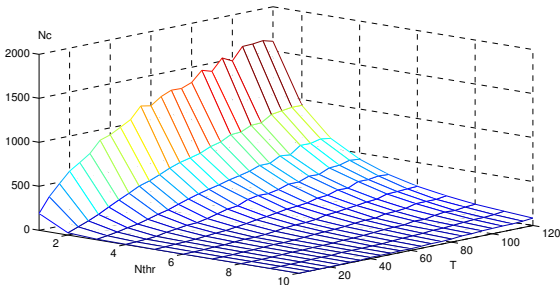


Fig. 3: The variation of N_c when T changes from 10s to 120s with step 10s and N_{thr} changes from 1 to 10 with step 1. The begin time of this duration is fixed at 8:00:00 April 18th, 2011.

From Fig.3, we can see that when the value of T is bigger and the value of N_{thr} is smaller, N_c becomes bigger. This trend is consistent with our expectation. Then we fix T , and to see the variation of N_c following the advance of

time with different values of N_{thr} . The result is shown in Fig.4. As we can see, when N_{thr} increases, the value of N_c decreases. Also, the value of N_c has peaks and valleys. These phenomena show us the coverage incompleteness of vehicular crowdsensing data.

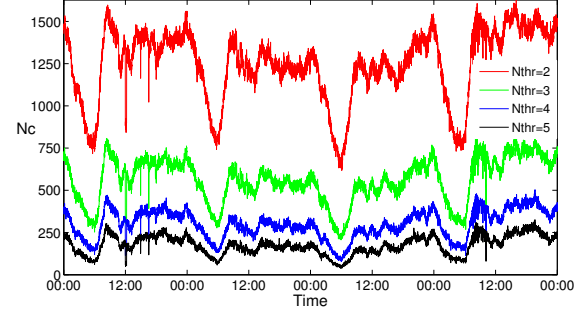


Fig. 4: The variation of N_c with the advance of time at fixed $T = 60s$ and $N_{thr} = 2, 3, 4, 5$ respectively. The time duration is from April 22th 00:00:00, 2011 to April 26th 00:00:00, 2011.

IV. OUR DESIGN OF STC

In this section, we first give an overview of STC. Then we introduce our strategy for GPS map-matching. Next we explain our methods for single road travel speed calculation and global travel speed vacancy completion.

A. Overview of STC

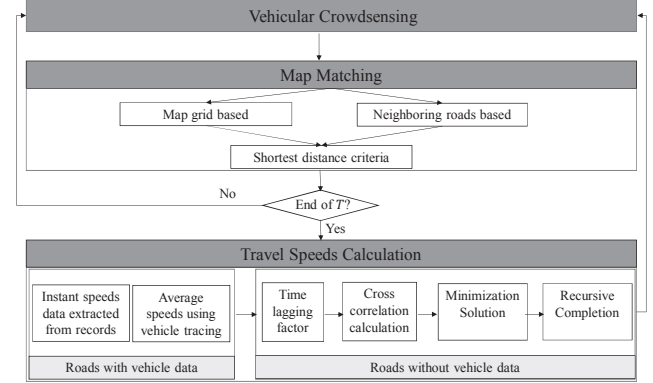


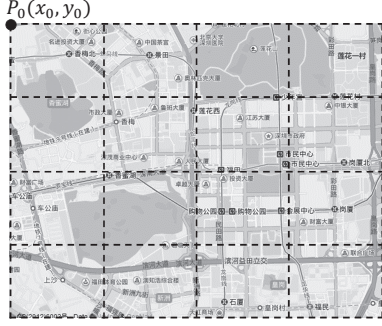
Fig. 5: An overview of STC.

The overview of STC is shown in Fig.5. In STC, every time a record is uploaded by vehicular crowdsensing, the GPS information will be extracted from the record and mapped to its corresponding road on map, where we use grid index of roads and vehicle tracking to accelerate map-matching. When a calculation interval ends, travel speeds of roads where vehicle data is available are calculated by combining instant vehicle speed that is extracted from uploaded records and vehicle tracking based average speeds. Coverage vacancies arise after this, so for the roads without vehicle data, spatial-temporal correlation among travel speeds is considered to fill up these vacancies, in which we make the determination of time lagging factor in cross correlation calculation self-adaptive. Then, we reduce the single-road travel speed vacancy completion problem to a minimization problem using the local-stationarity of cross

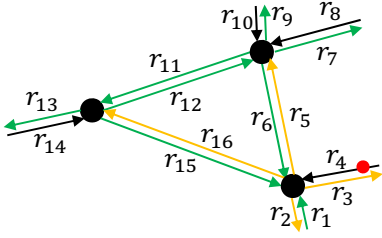
correlation. Finally, we fulfill global coverage completion in a recursive way.

B. Map-Matching

The goal of map-matching is to project a GPS location to a road segment accurately. There are two problems we have to handle. The first is the noise contained in GPS data, outliers for example. The second is that there is a large amount of roads as the candidates of a GPS location at the beginning of matching.



(a) Grid split of map.



(b) Vehicle tracing based candidate roads selection.

Fig. 6: Grid and vehicle tracing based map matching.

To eliminate the noise in GPS data, we use a constrained shortest distance to find the fittest road segment for P . We give a minimum distance D_{min} . If the distances between P and any segments are bigger than D_{min} , we reckon that P is an outlier and we will drop it.

To handle the candidate choosing problem, we first split the map into grids and index road segments to the grids. An illustration of this split is shown in Fig.6(a). Note that there are many roads that cross through more than one grids. Therefore, one road segment can belong to more than one grids. Assume that the coordinate of the point at the top left corner is $P_0(x_0, y_0)$. When we need to locate a GPS location $P(x, y)$, we first calculate the grid it belongs to. Assume this grid is g . Then we check the road segments indexed in g one by one to find the road segment that P belongs to.

We can see that there is a tradeoff between grid size and storage cost. If the grid size is too small, it will take us too much space to store the information of index structure. And if grid size is relatively big, the number of roads we have to check seriatim also becomes big. In this circumstance, we propose a vehicle tracking based method to fulfill map-matching. Our key idea is that if the time difference between two successive locations of a vehicle is small, a vehicle can't run for long distance. Assume that

the vehicle now locates at road segment r , with the help of outward neighbors (an outward neighbor of a road segment r is a road segment that takes r 's exit as its own entrance), we can take the outward neighbors and recursively the outward neighbors of these outward neighbors as candidate road segments. Fig.6(b) shows an example of this strategy. The red point in Fig.6(b) is the last location of vehicle v , it locates on r_4 , so the first class candidate roads for the next location of v are the yellow ones, which are the direct outward neighbors of r_4 , and the second class of that is the green ones which are the outward neighbors of the yellow ones.

C. Travel Speed Calculation & Vacancy Completion

Now we introduce the way we calculate travel speeds for the roads where vehicular data is available, measure spatial-temporal correlations and explain how to deal with travel speed vacancies.

1) Travel Speed Calculation for Roads with Available Vehicular Data:

At the end of current calculation interval, the accumulation of records for this interval is finished. So we can calculate travel speeds for road segments that are covered according to Definition 1. For later use, we define the network distance between two points P_1 and P_2 as,

Definition 2: $dist(P_1, P_2)$ is the distance walking from P_1 to P_2 along the shortest lawful driving path between them.

Then we define,

Definition 3: The *central point* of a road segment r , denoted as $cp(r)$, is the point that at the central location of r , when walking along r from its entrance to exit.

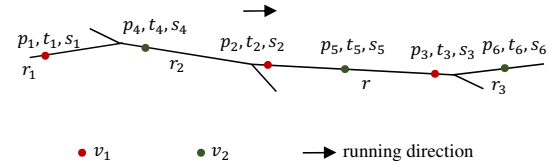


Fig. 7: Road segments and vehicle locations.

We take the situation shown in Fig.7 as an example to illustrate our calculation strategy. Assume the end time of current interval is t_e , so its begin time is $t_b = t_e - T$. Suppose that vehicle v_1 runs from location p_1 to location p_2 , then to p_3 , and vehicle v_2 runs from p_4 to p_5 , then to p_6 . The value s_i is the instant speed of the vehicle at its corresponding location. Assume that $t_1, t_4 < t_b$, and $t_2, t_3, t_5, t_6 \in [t_b, t_e]$, and there is no other vehicle on r during $[t_b, t_e]$.

We then calculate the two-phase average speeds of v_1 from p_1 to p_3 as,

$$\overline{s}_{1_1} = dist(p_1, p_2)/(t_2 - t_1), \overline{s}_{1_2} = dist(p_2, p_3)/(t_3 - t_2).$$

Similarly, the average speeds for v_2 from p_4 to p_6 are,

$$\overline{s}_{2_1} = dist(p_4, p_5)/(t_5 - t_4), \overline{s}_{2_2} = dist(p_5, p_6)/(t_6 - t_5).$$

Then, we give the average speed for r in this interval T as,

$$S = (\overline{s}_{1_1} + \overline{s}_{1_2} + \overline{s}_{2_1} + \overline{s}_{2_2} + s_2 + s_3 + s_5 + s_6)/(4 + 4),$$

where the first integer 4 in denominator is the number of average speeds calculated above, and the second 4 is that of speeds extracted from records that are right on r .

As demonstrated, we composite the instant speeds reported by vehicles and the average speeds calculated by locations and timestamps to generate the average speed for r . This composition leverages both explicit and implicit information of vehicular data.

2) Cross Correlation Function:

The traffic features at upstream and downstream road segments are correlated. In our paper, this feature is travel speed. We use time-lagged cross correlation function to quantize this correlation. Cross correlation function measures the inter-relevance between two vectors. We use Fig.7 to explain our cross correlation calculation procedure. In Fig.7, r_1, r_2 are upstream road segments to r , and r_3 is a downstream road segment from r . Denote the travel speed of r_1 at j^{th} calculation interval as x_j . Suppose that on average, vehicles on r_1 spend k calculation intervals to run from the central point of r_1 to the central point of r . We call the number k as the *time lagging factor*. Then we denote y_{j+k} as the travel speed of r at $(j+k)^{th}$ calculation interval. We use X and Y to represent the random variable forms of x and y respectively. Then the cross correlation between X and Y is,

$$c(X, Y) = \frac{\gamma_{XY}(k)}{\sigma_X \sigma_Y}, k = 0, \pm 1, \pm 2, \pm 3, \dots \quad (1)$$

where $\gamma_{XY}(k) = E[(x_j - \mu_x)(y_{j+k} - \mu_y)]$, with μ_x and μ_y being the means of X and Y . σ_X, σ_Y are the standard deviations of X and Y .

A proper use of cross correlation function requires that the random variables X and Y satisfy stationarity condition. In travel speed's sense, it means that the travel speed of a road segment r fluctuates around a constant value. According to life experiences, we observe that for a road, its travel speed can't satisfy stationarity for long time as a consequence of the variation of traffic pattern. However, travel speed can satisfy it within a short period of time. We denote the length of slide window as W . It contains integral number of calculation intervals, which is denoted as $w = W/T$. More convincingly, we show our statistical result of the travel speeds variation of a road in central city with different w in Fig.8. It shows the stationarity of travel speeds.

3) Vehicle Tracking Based Self-adaptive Time Lagging Factor Determination:

In order to calculate the travel speed cross correlation between two road segments accurately, the time lagging factor k between them must be determined properly. We denote the time lagging factor between two road segments u, r as $k_{u,r}$. Note that during different time of the day, $k_{u,r}$ also differs. For example, at morning peak, $k_{u,r}$ is bigger than that of midnight due to traffic congestion at morning. Therefore, it is necessary to determine $k_{u,r}$ for different time adaptively.

Novelly, we use the vehicle tracking to determine $k_{u,r}$. By recording the locations of a vehicle at different timestamps, we can obtain the time consumption for this vehicle to run from u to r . Then by tracking a certain number

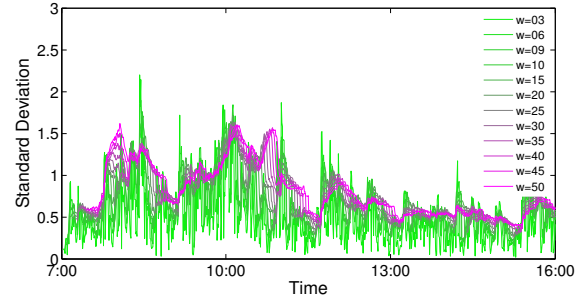


Fig. 8: The standard deviations of travel speeds for different length of w when time advances. Here, we set $T = 60s$. We can see that the standard deviations are relatively low. And these values first decrease and then increase when w increases.

of such vehicles, we can estimate $k_{u,r}$ in average sense. Specifically, we record the vehicles ever run on r in the time duration of W . We put these vehicles in set V_r . As the upstream of r , there are some vehicles in V_r that ran from u . By checking records, we select out vehicles satisfying this criterion and put them in set $V_{u,r}$. Note that the corresponding timestamps when vehicles in $V_{u,r}$ on u may be prior to the beginning of W . For every vehicle v in $V_{u,r}$, it has at least one record on u and at least one on r . For u , we select the record whose location is nearest to the central point of u . If more than two of them are selected, we further select the record whose timestamp is the biggest. We call this selection strategy as $s'(v, u)$. For r , we select the record whose location is nearest to the central point of r while its timestamp is the smallest one in multiple records which satisfy this criterion. We call this selection as $s''(v, r)$. With these two kinds of selection results of each $v \in V_{u,r}$, we then calculate average speed for v from u to r as,

$$avg(u, r, v) = \frac{dist(loc(s''(v, r)), loc(s'(v, u)))}{time(s''(v, r)) - time(s'(v, u))}.$$

Then we calculate the travel time of v from $cp(u)$ to $cp(r)$ at the speed of $avg(u, r, v)$, namely,

$$travelT(v) = dist(u, r) / avg(u, r, v).$$

With the values of $travelT(v_i)$, we have the estimation of $k_{u,r}$ as,

$$k_{u,r} = floor \left(\frac{\sum_{i=1}^{|V_{u,r}|} travelT(v_i)}{|V_{u,r}| * T} \right).$$

where $floor(\cdot)$ gives the value of the floor of a decimal.

Therefore, through vehicle tracking, we get the estimation of the time lagging factor between two road segments during W . To show the feasibility of this estimation method, we illustrate the cross correlation calculation results between two roads that are selected in central city for our $k_{u,r}$ and predefined time lagging factors in Fig.9. It shows that compared with predefined time lagging factors, the $k_{u,r}$ determined by our method gives more evident cross correlation values.

However, it is noteworthy that the most proper value of k does not necessarily correspond to the highest value of

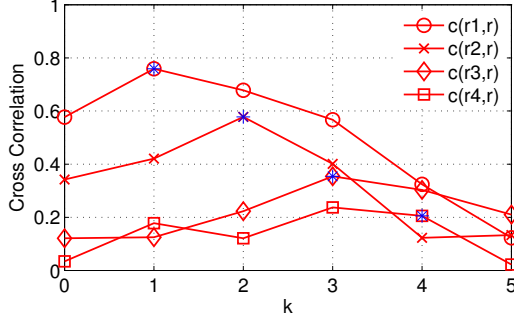


Fig. 9: The comparison of the values of $k_{u,r}$ between our estimation method and the predefined values (i.e. 0-5). These roads r_1, r_2, r_3, r_4 and r are selected in central city of Shenzhen. The values of k s corresponding to blue stars in this figure are the estimated time lagging factor values by our method. It can be seen that our method usually estimates the most proper k s that corresponding to highest cross correlation values. The value of T is 60s, and the value of w is set to 10. The time expansion of this figure is from 8:00:00 to 9:00:00 in April 18th 2011.

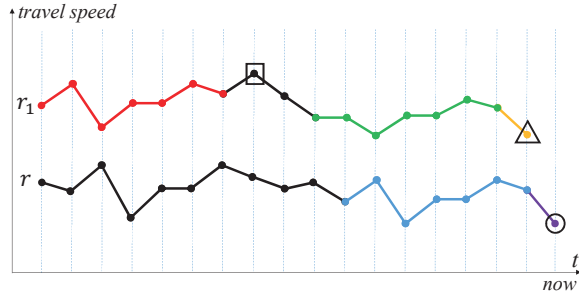


Fig. 10: An explanation for the choice of k . The travel speed value in purple (surrounded by a circle) in Fig. 10 needs to be estimated. Here $w = 7$. So, if we search for the travel speed value sequence in r_1 's values which has the biggest cross correlation with the blue ones in r 's values, we will locate to the red sequence. Then the purple value will be estimated in reference of the value that surrounded by a rectangle. However, the rectangle one has increased from the last red one, while the purple one is lower than the last blue one. So their trends are not the same. Differently, though the green sequence has a lower cross correlation with the blue one, the value in yellow (surrounded by a triangle) decreases after the last green value, which is similar to the trend of the purple one.

cross correlation. Fig.10 illustrates the explanation for this. This is why we don't use a traversal way to find the lagging time corresponding to the highest cross correlation as the k we need.

4) Travel Speeds Estimation for Roads Where Vehicular Data Is Unavailable:

(1) A Minimization Problem for Single-Road Vacancy

In section IV-C1, we showed our method of travel speed calculation for roads where data for current calculation interval is available. Now we handle single-road vacancy by using cross correlation function. First, we define,

Definition 4: $X(index_1, index_2)$ is the sub-vector of vector X from the subscript $index_1$ to the subscript $index_2$. And $X(index)$ is the item at the location $index$ which begins from 1. For example, if $X = [1, 3, 5, 7, 9]$, then $X(2, 3)$ gives $[3, 5]$, and $X(3)$ gives 5.

Suppose that current calculation interval is the n^{th} one from the beginning of \mathcal{T} , and now we want to fill the

vacancy of the current travel speed for road r . Denote the area in which the roads we will consider to help to calculate the travel speed for r as A_r , and denote the upstream roads of road r within A_r as $R_r = \{r_1, r_2, r_3, \dots\}$. We then calculate the cross correlations between every r_i and r .

Denote the travel speed vector for r_i from the 1st to the n^{th} interval in \mathcal{T} as X_{r_i} , and that for r as X_r . As introduced in section IV-C3, we can estimate the time lagging factor from r_i to r . Then for any $r_i \in R_r$, the cross correlation between r_i and r during last W which starts at $(n-w)^{th}$ and ends at $(n-1)^{th}$ calculation interval can be calculated as,

$$c_{pre}(r_i, r) = c(X_{r_i}(n - k_{r_i, r} - w, n - k_{r_i, r} - 1), X_r(n - w, n - 1)). \quad (2)$$

Fig. 11 illustrates the interval selection for the calculation of $c_{pre}(r_i, r)$.

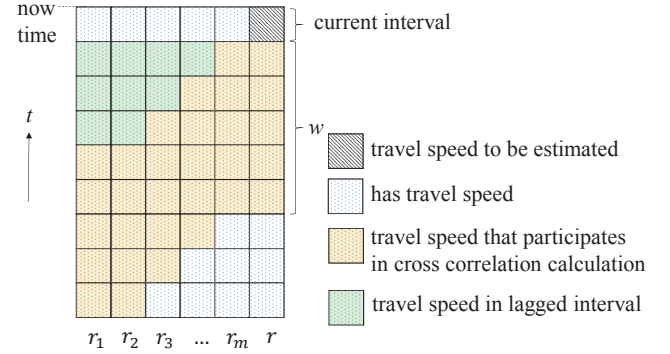


Fig. 11: The interval selection to calculate $c_{pre}(r_i, r)$. Here $k_{r_1, r} = 3$, $k_{r_2, r} = 3$, $k_{r_3, r} = 2$, $k_{r_m, r} = 0$.

Similarly, the cross correlation between r_i and r during W which starts at $(n-w+1)^{th}$ and ends at n^{th} calculation interval can be expressed as,

$$c_{now}(r_i, r) = c(X_{r_i}(n - k_{r_i, r} - w + 1, n - k_{r_i, r}), X_r(n - w + 1, n)). \quad (3)$$

We illustrate the interval selection of the calculation of $c_{now}(r_i, r)$ in Fig.12. It is noteworthy that $c_{now}(r_i, r)$ contains the unknown quantity $X_r(n)$.

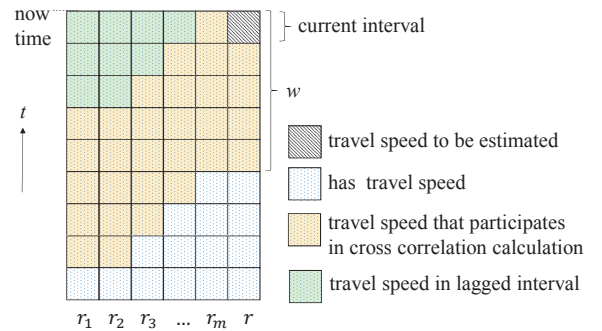
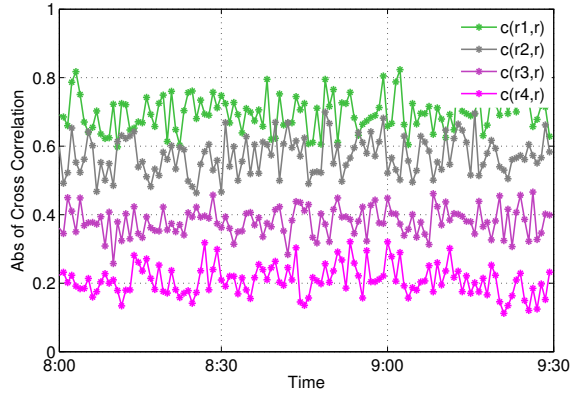
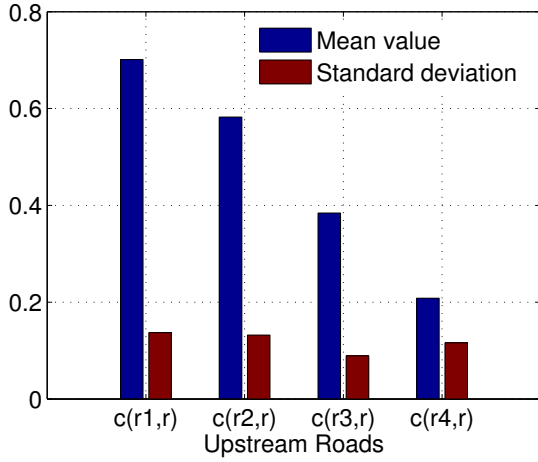


Fig. 12: The interval selection to calculate $c_{now}(r_i, r)$.

Let vector $C_{pre}(r) = [c_{pre}(r_1, r), c_{pre}(r_2, r), \dots]$ denote the values of $c_{pre}(r_i, r)$ between every r_i and r . And



(a) The changes of cross correlations between different roads and r when time advances. We can see that the cross correlation value between road pairs fluctuates in a small range.



(b) The mean value and standard deviations of the cross correlations shown in Fig.13(a). It can be seen that the standard deviations are small, which indicates the stationarity of cross correlations.

Fig. 13: The illustration of the stationarity of travel speeds cross correlation between roads.

put the values of $c_{now}(r_i, r)$ between every r_i and r in vector $C_{now}(r) = [c_{now}(r_1, r), c_{now}(r_2, r), \dots]$.

We observe that the cross correlation of travel speeds between roads also meet stationarity demand, which is shown in Fig.13 as an example. So we can estimate the value of the current travel speed $X_r(n)$ for r by minimizing the differences between $C_{pre}(r)$ and $C_{now}(r)$, namely,

$$obj = \min_{X_r(n)} \|C_{now}(r) - C_{pre}(r)\|_2, \quad (4)$$

i.e.

$$obj = \min_{X_r(n)} \left\{ \sum_{i=1}^m [c_{now}(r, r_i) - c_{pre}(r, r_i)]^2 \right\}^{\frac{1}{2}},$$

where m is the number of r_i s. We then let

$$f(X_r(n)) = \sum_{i=1}^m [c_{now}(r, r_i) - c_{pre}(r, r_i)]^2,$$

so the minimization of obj is equal to the minimization of $f(X_r(n))$. For the simplicity of presentation, we let $Y_{r_i} = X_{r_i}(n - k_{r_i, r} - w + 1, n - k_{r_i, r})$, and $Y_r = X_r(n - w + 1, n)$,

where $Y_r(w) = X_r(n)$. Then f can be further formulated as,

$$f = \sum_{i=1}^m \left[\frac{E[(y_r - \mu_{Y_r})(y_{r_i} - \mu_{Y_{r_i}})]}{\sigma_{Y_r} \sigma_{Y_{r_i}}} - c_{pre}(r, r_i) \right]^2.$$

We then let

$$g_i(X_r(n)) = E[(y_r - \mu_{Y_r})(y_{r_i} - \mu_{Y_{r_i}})],$$

and

$$h(X_r(n)) = \sigma_{Y_r} \sigma_{Y_{r_i}},$$

where $X_r(n)$ exists in y_r , μ_{Y_r} and σ_{Y_r} . So f can be shown in a simpler way as,

$$f = \sum_{i=1}^m \left[\frac{g_i}{h} - c_{pre}(r, r_i) \right]^2.$$

And the derivative of f in terms of $X_r(n)$ is,

$$f' = 2 \sum_{i=1}^m \left[\frac{g_i}{h} - c_{pre}(r, r_i) \right] \frac{g'_i h - g_i h'}{h^2 \sigma_{Y_{r_i}}}. \quad (5)$$

Then by letting $f' = 0$, the value of $X_r(n)$ at which obj reaches its minimum can be obtained.

(2) A Recursive Way for Global Vacancies Completion:

Having the method for single road travel speed vacancy completion, we now fill all the vacancies of roads by using it in a recursive way.

As aforementioned, we use A_r to limit the number of upstream road segments that help to calculate the current travel speed for r . More specifically, we use limited backtracking method to fulfill this aim. We set a distance threshold d_A by combing network distance $dist()$ and the intersection distance $distI(u, r)$ between road segment u and r is the number of intersections between them along the path of their network distance $dist(u, r)$. For example, $distI(r_1, r_3)$ in Fig.7 is three. We use the product of intersection distance and network distance to limit A_r , $Dist(u, r) = dist(u, r) \times distI(u, r)$. Only when $Dist(r_i, r) \leq d_A$, the upstream road segment r_i should be taken into consideration to calculate the travel speed for r .

The use of cross correlation function is based on the assumption that the current interval travel speed values for every $r_i \in R_r$ are available, but in reality it is inevitable that some of them are also empty. Note that when traffic is under low pressure, the sparsity of vehicular data also becomes serious. So we define a threshold N_{min} . When the number of road segments having travel speeds contained in R_r , denoted as N'_{R_r} , satisfies $N'_{R_r} \geq N_{min}$, we stipulate that the calculation for r can be continued, which means that we only use the roads having travel speeds in R_r to calculate the travel speed for r . We only calculate the cross correlations between them and r . When N'_{R_r} satisfies above criterion, we say that r is *calculable*.

Now, we use a recursive algorithm to fill global travel speed vacancies. We start from a road segment r which has no travel speed for current interval. Then we check each road segment $r_i \in R_r$ one by one from vicinity to remote. If r is calculable, we simply calculate its travel speed with the help of R_r . If R_r contains any r_i that does not have

travel speed, we put them in R'_r . For every $r_i \in R'_r$, we take it as a road whose travel speed need to be filled one by one also from vicinity to remote, and check R_{r_i} and R'_{r_i} for it. We show the whole algorithms for travel speeds completion in Alg.1 and Alg.2.

Algorithm 1 $TS_All(\mathcal{R})$: Travel speeds calculation of \mathcal{R} .

Input: The edge set \mathcal{R} of \mathcal{G} .

Output: The estimated travel speeds for every $r \in \mathcal{R}$.

```

for each  $r \in \mathcal{R}$  do
  if  $X_r(n)$  is not calculated then
    if  $r$  has records for current interval then
      Calculate  $X_r(n)$  using method introduced in section IV-C1;
    else
      call  $TS(r)$ ;
    end if
  end if
end for

```

Algorithm 2 $TS(r)$: Travel speed filling-up for r .

Input: Road segment r .

Output: The estimated travel speed $X_r(n)$ for r .

```

stack  $S \leftarrow \emptyset$ ;
if  $r$  is calculable then
  calculate  $X_r(n)$ ;
else
  push( $S, r$ );
  for each  $r_i \in R'_r$  do
    call  $TS(r_i)$ ;
  end for
  calculate  $X_r(n)$ ;
  pop( $S, r$ );
end if

```

(3) Initialization of Our Algorithm

Note that our estimation method requires that at the n^{th} interval, the travel speeds of past $w - 1$ calculation intervals are all available for every $r \in \mathcal{R}$. So, when $n \leq w$, we have to fill up the vacancies in another way. We do this by averaging the history values. If no value was calculated in history, we set the value as a properly high speed because no data always means little number of vehicles running on road, which usually means a good traffic condition. This is the initialization procedure of our strategy.

(4) Parallelization of Our Algorithm

With the purpose of accelerating the calculation speed of global travel speeds completion using our recursive algorithm, we can divide the whole area of city to several un-overlapped regions whose size are similar. Then in each of these regions, we choose a road as its starting location of recursive algorithm. By doing so, our method can be executed in a parallelized way. The feasibility of this parallelization is guaranteed by the wide spatial distribution of vehicles.

V. EXPERIMENTAL EVALUATION

In this section, we illuminate the superiority of our travel speed calculation method by comparing its estimation errors with classical methods.

A. Estimation Error Measurement

Suppose that $\mathcal{S} = [s_1, s_2, \dots]$ contains the ground truth values of travel speeds for every road segment in \mathcal{R} , and $\mathcal{S}' = [s'_1, s'_2, \dots]$ contains the estimated values of these travel speeds. The relative error of \mathcal{S}' to \mathcal{S} is the relative difference between them,

$$\varepsilon(\mathcal{S}, \mathcal{S}') = \frac{\|\mathcal{S}' - \mathcal{S}\|_2}{\|\mathcal{S}\|_2} = \frac{(\sum_{i=1}^{|\mathcal{S}|} |s'_i - s_i|^2)^{\frac{1}{2}}}{(\sum_{i=1}^{|\mathcal{S}|} s_i^2)^{\frac{1}{2}}}.$$

B. Travel Speed Estimation Results

As introduced, the calculation of estimation error needs ground truth. The real ground truth of travel speeds for roads is unavailable. So we use cross validation instead. We set the ground truth by picking up an experiment time duration in which the coverage ratio of roads is high. Then we randomly hide some travel speeds for some roads with a predefined missing ratio. Then we recover these missing(hidden) values by our completion strategy and comparative methods and then calculate their estimation errors respectively. Based on experimental analysis, the experiment duration we select is 7:00:00-16:00:00 April 24th, 2011, which averagely has 1512 out of 1882 roads covered by vehicles during every interval when $N_{thr} = 2$. There are two reasons why we take 2 as the value of N_{thr} . Firstly, the sampling data collected by probe taxis is so coarse that the number of taxis running through a road segment is not big for a relative short interval, as we have shown in section III-B. Secondly, if we take 1 as N_{thr} , it is not representative enough to implement our methods for the travel speed and time lagging factor calculation.

Before comparison, we should determine important parameters T and w because different combinations of their values give quite different estimation errors. We determine them by averaging the estimation errors corresponding to ten randomly chosen separated hours from the whole time expansion in data set. Fig.14 shows the average errors at different T and w when the missing ratio is 0.2. It can be seen that when $T = 80s$ and $w = 12$, the average estimation error is the lowest. Other missing ratios give similar suggestions.

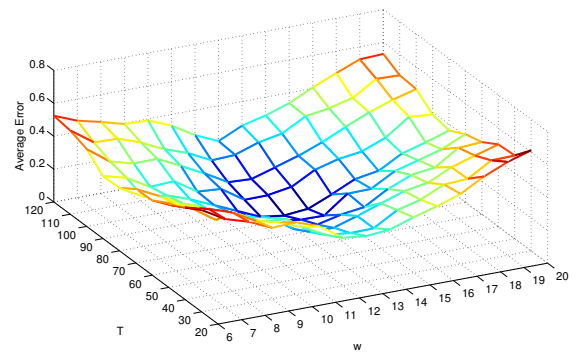


Fig. 14: We randomly choose ten separated hours from the whole time expansion and calculate the average estimation error when the missing ratio is 0.2. Here, $d_A = 2000m$, $N_{min} = 4$.

Now we introduce the estimation methods that we will compare with.

•*Kriging* is a spatial interpolation method that builds variation function model according to the spatial location relation among data [19] [20]. Based on this variation function, Kriging interpolates the missing data using the correlation between the locations that have and not have data. It is a well-known data recover method but it mainly focuses on spatial relations of data at different locations.

•*KNN* uses the weighted average values of the K nearest locations to the location whose data to be estimated as the estimation value. Here we take the inverse of distance as weighting basis. The nearer is a location to the location to be estimated, the bigger its weight will be. And here we use 4 as the number N , as is always used in the literature.

•*ARIMA* (Autoregressive Integrated Moving Average Model) is a famous time series analysis based prediction method that regresses the dependent variable with regard to its lagging value and the present as well as lagged values of random error to establish models. It mainly considers the temporal relations among data [21]. Here we use the values in past $w - 1$ intervals to estimate the values in n^{th} interval.

Fig.15 shows the estimation errors of STC, Kriging, KNN, and ARIMA for every calculation interval in the experiment duration. The missing ratio in Fig.15 is set to 0.2. We can see that STC makes the lowest errors at most of the intervals. And to observe the robustness of STC when the missing ratio varies, we show the average estimation error of travel speeds of all the intervals in the experimental duration in Fig.16. We can see that when the missing ratio is smaller than 0.7, STC always get the lowest errors among the four algorithms.

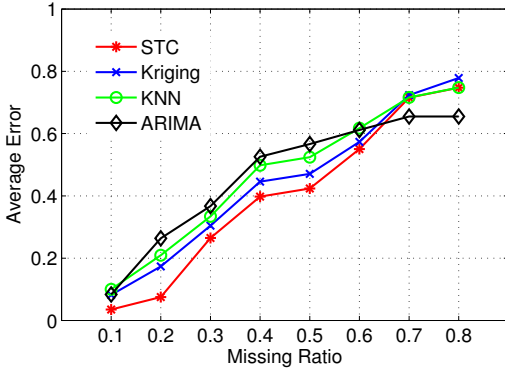


Fig. 16: The average errors for different missing ratios when interval $T = 80s$, $w = 12$.

C. An Extension for Future Travel Speed Prediction

Besides current interval travel speed calculation, predicting future travel speed also has great meaning for trip planning, transportation management, etc.. Our method can also be used for travel speed prediction for next calculation interval with a modification.

1) Our Method for Predicting Future Travel Speeds:

Different from current interval travel speed estimation, the future travel speed prediction is based on the condition that all the values for current calculation interval is calculated but none of travel speeds for next interval is available. In

this situation, we can predict travel values by a weighted averaging method.

Since no travel speed information in next interval is available, and the cross correlation function calculated only measures the correlation till current interval, to predict travel speed in next interval, we can only use the roads from which the lagging factor to r is bigger than 0. We pick up these road segments from R and denote the set containing them as R_0 . For every $r_i \in R_0$, we have its corresponding $c_{now}(r_i, r)$. The value $c_{now}^2(r_i, r)$ indicates the *coefficient of determination* that we can estimate the values of travel speeds for r using the travel speed values of r_i . The weight we are about to use is,

$$\omega(r_i, r) = c_{now}^2(r_i, r) / \sum_{i=1}^{|R_0|} c_{now}^2(r_i, r)$$

We then use linear regression to get the relationship between the travel speeds of r_i and r . The regression result can be formulated as $X_r = a_i X_{r_i} + b_i$. Therefore, the predicted travel speed of r for next interval is,

$$X_r^+(n+1) = \sum_{i=1}^{|R_0|} ((a_i \times X_{r_i}(n - k_{r_i, r} + 1) + b_i) \times \omega(r_i, r)). \quad (6)$$

Fig.17 shows our interval selection for prediction.

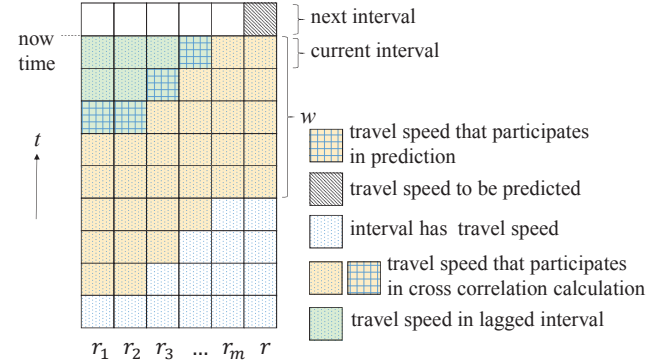


Fig. 17: Interval selection for travel speed prediction.

2) Future Travel Speeds Prediction Results:

In future travel speeds prediction, we can use the next interval estimation results calculated using next interval vehicular data as ground truth. However, we still should determine the parameters T and w first. And similarly, we randomly choose ten separated hours in the experiment duration and change the values of T and w . Fig.18 shows the results of this procedure. We can see that STC gets the lowest error when $T = 90s$, and $w = 13$.

Then we compare the the prediction error of STC with two classical prediction methods:

•*KF* (Kalman Filter) is a theoretically optimal data processing algorithm [14] [22] [23]. It combines the values of last condition time and the current condition value and minimizes the mean of squared error. It can be used to predict system condition with favorable accuracy.

•*ARIMA* which was introduced before. In the literature, e.g. Voort *et al.* [21] used ARIMA time series models to forecast traffic flow.

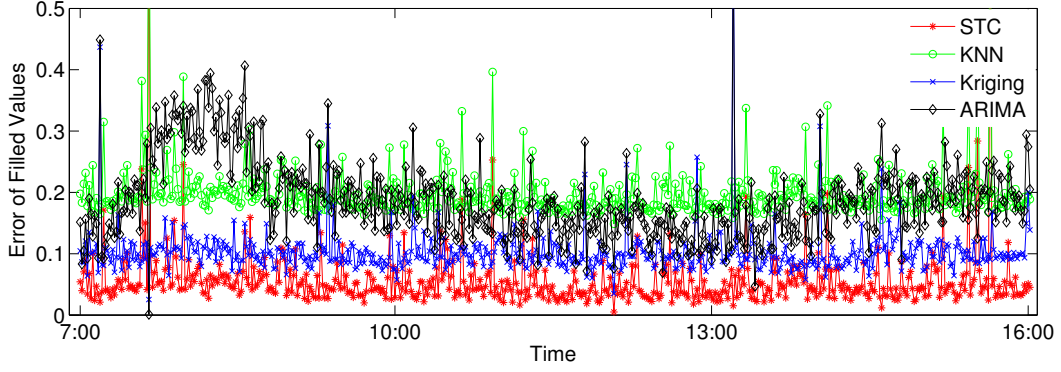


Fig. 15: The comparison of filling-up errors among four estimation methods during 7:00-16:00 April 24th, 2011. The missing ratio is 0.2. And $T = 80s$, $w = 12$.

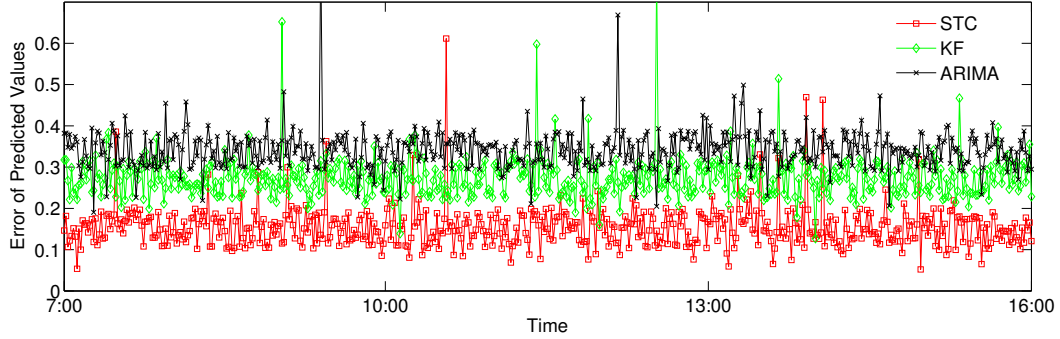


Fig. 19: The prediction errors of STC, KF, and ARIMA. STC always gives the lowest errors among three methods.

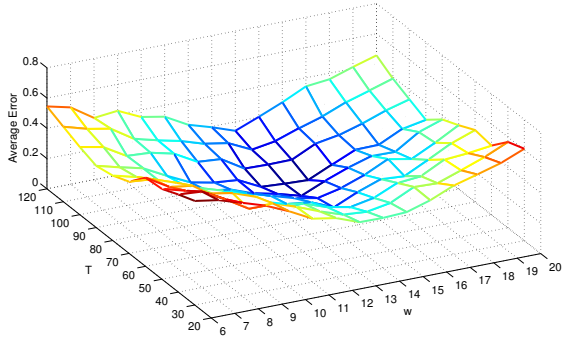


Fig. 18: The average prediction errors of ten randomly chosen hours at different T and w when the missing ratio is 0.2.

The comparison result is shown in Fig.19 from which we can see that among three methods, our method always gives lowest errors in all the calculation intervals.

VI. CONCLUSION AND FUTURE WORK

In this paper, we propose a new vehicular crowdsensing data based travel speed calculation strategy called STC to estimate travel speeds. We use cross correlation to measure the spatial-temporal correlations of travel speeds among different road segments. When calculate cross correlation, we novelly use vehicle tracking to self-adaptively determine the time lagging factors of travel speed diffusion between roads. We settle the problem of single-road travel speed vacancy completion via reducing it to a minimization prob-

lem, using the local-stationarity of cross correlation. Then we fill up all the vacancies in a recursive way by utilizing the geometrical structure of road net. Experiments based on real vehicle data show that our strategy estimates travel speeds with lowest errors when compared with classical methods. And also, we show that our method can be easily transferred to predict travel speed for future calculation interval. In the future, we will pay more attention to the issues of wireless communication cost (e.g. bandwidth consumption) saving and privacy protection in our design.

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